Optimization of well field management

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Preface

The work reported in this PhD thesis, entitled "Optimization of well field management", was conducted at the Department of Environmental Engineering, Technical University of Denmark. The work was carried out under the supervision of Professor Dan Rosbjerg, with Associate Professor Peter Bauer-Gottwein and Dr Henrik Madsen (DHI Water - Environment - Health) as co-supervisors.

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The thesis consist of a synopsis and three scientific journal papers. In the synopsis the papers are referred to by their roman number, e.g. as "Paper II".

I. Hansen, A.K., Hendricks Franssen, H.J., Bauer-Gottwein, P., Madsen, H., Rosbjerg, D., Kaiser, H.P. *Well Field Management Using Multi-Objective Optimization*, submitted manuscript, February 2011.

II. Hansen, A.K, Madsen, H., Bauer-Gottwein, P., Falk, A.K.V., Rosbjerg, D. *Multi-objective optimization of the management of a waterworks using an integrated well field model*, Hydrology Research, 2011, accepted

III. Hansen, A.K, Madsen, H., Bauer-Gottwein, P., Rosbjerg, D., Falk, A.K.V. *Optimization of well field operation: Case study Søndersø waterworks, Denmark*, submitted manuscript, June 2011

The papers are not included in this www-version, but can be obtained from the Library at DTU Environment:

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Finally thanks to Erik, my husband, who always have been there for me when things were difficult, and my two sons, Marius and Peter, who missed me when I was away for external stay, conferences and courses.

Summary

Groundwater is a limited but important resource for fresh water supply. Different conflicting objectives are important when operating a well field. This study investigates how the management of a well field can be improved with respect to different objectives simultaneously. A framework for optimizing well field management using multi-objective optimization is developed. The optimization uses the Strength Pareto Evolutionary Algorithm 2 (SPEA2) to find the Pareto front between the conflicting objectives. The Pareto front is a set of non-inferior optimal points and provides an important tool for the decision-makers. The optimization framework is tested on two case studies. Both abstract around 20,000 cubic meter of water per day, but are otherwise rather different.

The first case study concerns the management of Hardhof waterworks, Switzerland, where artificial infiltration of river water into infiltration basins and injection wells are essential for securing the production of drinking water. Inflow of contaminated water from surrounding urban areas is prevented, because the infiltration maintains a hydraulic gradient directed away from the well field. The objectives of the optimization problem are to minimize the amount of infiltration, and to minimize the risk of getting contaminated water into the production wells. The optimization problem is subjected to a daily demand fulfilment constraint.

Constant and sequential scheduling optimization is performed on the Hardhof case. The constant scheduling keeps all decision variables constant during the evaluation period. This method shows good performance when the hydrological conditions and water demand are relatively constant during the evaluation period. Compared with historical operations the optimization problem can be improved with respect to both objectives.

The sequential scheduling optimizes the management stepwise for daily time steps, and allows the final management to vary in time. The research shows that this method performs better than the constant scheduling when large variations in the hydrological conditions occur. This novel approach can be used in real-time operation of the waterworks, because the hydrological parameters for the model only have to be provided for one time step ahead. If the contamination risk is kept at the historical level both optimization methods show that it is possible to reduce the amount of infiltration water. It is also possible to reduce the contamination risk if the distribution of the infiltrated water is changed, so that more water is infiltrated in the basins and less in the wells. However, if the waterworks want to be sure to

avoid inflow of contaminated water it is necessary to increase the total amount of infiltration.

The second case study considers the operation of Søndersø waterworks, Denmark. At Søndersø the optimization objectives are to minimize the energy consumptions of the waterworks, and to minimize the risk of getting contamination from the nearby contaminated Værløse Airfield into the well field. The decision variables are the relative speed of the pumps. The waterworks has to provide a certain amount of drinking water.

A fully integrated hydraulic well field model, which predicts the flow of water in the aquifer, in the well, and in the pipe network has been developed. The well field model, WELLNES (WELL Field Numerical Engine Shell), is capable of predicting the power consumption at different wells. It captures the water level- and power dynamics in each well when pump speeds are changed. WELLNES is set up and calibrated for the Søndersø area. The WELLNES model shows good correspondence between observations and simulations in both calibration and validation periods.

The optimization results for Søndersø shows that only minor energy savings can be achieved with the existing pumps. If all the existing on/off pumps are changed to new variable-speed pumps it is, however, possible to save between 25 and 40% of the specific energy (the energy consumption per cubic meter of abstracted water). This corresponds approximately to an energy reduction of 200 MWh per year. All optimization results shows that it is possible to obtain significant reductions in the contamination risk. The research shows that the large potential for savings is mainly due to optimizing the variable-speed pumps rather than optimizing the new on/off pumps. The payback period of investing in new variable-speed pumps for Søndersø waterworks is only 3-4 years, which is an interesting time horizon for the waterworks.

The developed multi-objective optimization framework has shown to be useful in optimizing the management of well fields, and it has successfully been applied to the two case studies, Hardhof and Søndersø waterworks. If the method is applied to all Danish waterworks it is estimated that 20-32 GWh/year could be saved, corresponding to 17-27 million DKK.

Dansk sammenfatning

Grundvand er en vigtig, men ikke utømmelig kilde til forsyning af drikkevand. I forhold til kildepladsstyring findes der flere, og ofte modstridende, interesseområder. Dette Ph.d. projekt undersøger, hvordan kildepladsstyring kan forbedres med hensyn til forskellige beslutningsmål samtidigt, også kaldet multi-objektiv optimering. Der er udviklet en softwareplatform der bruger multi-objektiv optimering til at forbedre kildepladsstyringen. Optimeringen bruger "Strength Pareto Evolutionary Algorithm 2" (SPEA2) til at finde Pareto fronten mellem de modstridende beslutningsmål. En Pareto front er et sæt af ikke-dominerede optimale punkter, og er et vigtigt værktøj for beslutningstagere. Optimeringsplatformen er eksemplificeret og testet på to case studies, der begge indvinder cirka 20.000 kubik meter vand om dagen, men ellers er ret forskellige.

Det første case study handler om kildepladsstyring af Hardhof vandværk i Schweiz, hvor kunstig infiltrering af flodvand i infiltrations bassiner og injektions brønde er essentiel for at sikre drikkevandsproduktionen. Tilstrømning af forurenet vand fra omgivelserne forhindres af infiltrationen, der opretholder en hydraulisk gradient væk fra kildepladsen. Beslutningsmålene for optimeringen er at minimere mængden af infiltreret vand og at minimere risikoen for at få forurenet vand ind i produktionsbrøndene, imens der samtidigt skal leveres en daglig mængde drikkevand

Konstant og sekventiel optimering er blevet foretaget på Hardhof vandværket. Den konstante optimering holder alle beslutningsvariabler konstante i modelevalueringsperioden og fungerer godt, når de hydrologiske parametre og leveringskravet er relative konstante i evalueringsperioden. Resultaterne fra den konstante optimeringsmetode viser yderligere at kildepladsstyringen, sammenlignet med den historiske styring, kan blive forbedret med hensyn til begge beslutningsmål. Den sekventielle optimeringsmetode optimerer problemet skridtvis for daglige tids skridt, hvilket tillader den endelige løsning at variere i tid. Forskningen viser, at denne metode virker bedre end den konstante optimering, når der forekommer store variationer i de hydrologiske parametre. Desuden kan den sekventielle optimeringsmetode bruges ved real-tids operationer af vandværker, fordi de hydrologiske parametre til modellen kun skal leveres til et tids skridt frem i tiden. Resultaterne fra begge optimeringsmetoder viser, at hvis forureningstruslen holdes på det historiske niveau, er det muligt at spare på mængde af infiltreret vand. Det er også muligt at reducere forureningstruslen, hvis fordelingen af det infiltrerede vand ændres således, at mere vand bliver infiltreret i bassinerne og mindre i brøndene. Hvis

vandværket vil være sikre på at undgå tilstrømning af forurenet vand er det nødvendigt at øge den samlede mængde af infiltreret vand.

Det andet cast study handler om kildepladsstyringen af Søndersø vandværk i Danmark. Beslutningsmålene på Søndersø vandværk er at minimere vandværkets energiforbrug og at minimere risikoen for at få tilstrømning af forurenet vand fra den nærliggende forurenede grund, Værløse flyveplads. Beslutningsvariablerne er den relative hastighed af pumperne, mens vandværket skal levere en daglig mængde drikkevand. Der er udviklet en integreret hydraulisk kildepladsmodel, som forudsiger vandets strømning i grundvandsmagasinet, i brønden og i ledningsnettet. Kildepladsmodellen, WELLNES (WELL Field Numerical Engine Shell) kan forudsige effektforbruget i de enkelte brønde, og er i stand til at beregne de hurtige vandstands- og effektforbrugsændringer der sker i brøndene når pumpernes hastighes ændres. WELLNES er sat op og kalibreret for Søndersø vandværk. Der er god overensstemmelse mellem model simulering og observationer.

Optimeringsresultaterne for Søndersø vandværk viser at den besparelse, der kan opnås ved at bruge de eksisterende tænd/sluk-pumper er lille. Hvis alle de eksisterende tænd/sluk-pumper erstattes med nye hastighedsregulerbare pumper, er det muligt at spare mellem 25 og 40 % af det specifikke energiforbrug (energiforbruget per oppumpet mængde vand). Det svare til en reduktion i energiforbruget på cirka 200 MWh per år. Alle resultater viser, at der kan opnås en betydelig reduktion i forureningsrisikoen. Forskningen viser desuden, at det store energibesparelsespotentiale primært skyldes optimeringen af de hastigheds-regulerbare pumper frem for optimering af nye tænd/sluk-pumper. Tilbagebetalingstiden for at investere i de nye hastighedsregulerbare pumper til Søndersø vandværk er kun 3-4 år, hvilket er en interessant tidshorisont for vandværkerne.

Den udviklede softwareplatform til multi-objektiv optimering af kildepladsstyring har vist sig at fungere godt, og det er med succes blevet brugt på de to case studies, Hardhof og Søndersø vandværk. Hvis optimerings metoden benyttes på alle de danske vandværker estimeres det, at der kan opnås besparelser på 20-32 GWh/år, eller det der svare til 17 til 27 millioner kroner.

Contents

1 Introduction

Groundwater is a vulnerable and limited resource. We depend on groundwater for drinking and irrigation, and the industry needs water for production. Excessive abstraction can cause groundwater depletion, saltwater intrusion, and contamination of the wells, or the wells can simply dry out. Improved groundwater management can contribute to a sustainable groundwater exploitation that can supply the growing population of the Earth.

An important issue that has become a priority over the last decade, due to rising energy prices and global warming, is energy saving. A main objective of this research is to investigate how much energy can be saved, when the pumping operation of a waterworks is optimized.

On average 75% of the Danish waterworks' total energy consumption is used on production of water (Reschefski, 2009). In Denmark 99% of the fresh water consumption comes from groundwater, and the Danish waterworks abstracts around 406 mio m^3 of water per year (Thorling, 2010). Even a small reduction in the specific energy [kWh/m^3] will lead to large overall savings.

The other main objective considered in this research is protection of the well fields from intrusion of contaminated water from surrounding contaminated sites. During the last 10 years, more than 100 drinking water wells in Denmark have been closed due to contamination (Thorling, 2010). Even more wells are threatened by contaminated sites close to the well fields. Once a well is contaminated, there is often no other option than to close the well.

Other important objectives in groundwater management are water quality, reliability of supply, and consideration of the aquatic environment.

The different objectives are often conflicting, so that minimizing one objective will increase another. Multi-objective optimization is a method that finds a set of non-dominated solutions, i.e a set of solutions where no solution is better than any of the others with respect to all objectives. The set of non-dominated solutions is called the Pareto front and is a useful management tool for the decision-makers. They can choose a solution on the Pareto front, knowing that it is an optimal solution, and knowing the objective function values.

This research uses multi-objective optimization to solve two well field management problems.

The first case considers the management of a waterworks in Zurich, Switzerland. The waterworks abstracts water from an aquifer that is artificially recharged with river water. The infiltrated water creates a barrier towards a contaminated area next to the waterworks. The two conflicting objectives in this study are to minimize the infiltration and to minimize the risk of getting contamination into the production wells. The case study is presented in Paper I including a real-time operation approach.

The second case study is a Danish waterworks which also has a contaminated site as neighbour. The two conflicting objectives are to reduce the energy consumption and to minimize the contamination risk. A well field model is set up and presented in Paper II. The model predicts the hydraulic state variables in and around the waterworks, and calculates the energy consumption of the waterworks. The well field model is used to improve the management through multi-objective optimization. First, optimization of the waterworks' current on/off pump settings is performed. Second, the management is optimized by considering installation of new variable-speed pumps. Paper III describes the optimization problem and also discusses the payback period of the investment for buying new pumps.

The thesis consists of a synopsis and the three papers, Papers I, II, and III. The synopsis contains the following chapters; chapter 2 gives a literature review of groundwater management and evolutionary algorithms used in groundwater management; chapter 3 introduces the two case studies and the well field model; chapter 4 contains the methodology; chapter 5 contains the main results and discussion of these; chapter 6 presents the concluding remarks.

2 Literature review

This chapter reviews relevant scientific literature. Section 2.1 reviews different types of groundwater management problems, and section 2.2 reviews the different methods used to solve the groundwater management problems.

2.1 Groundwater management problems

Extensive research has been performed in groundwater remediation and monitoring design, where the goal is to secure the area around a contaminated site by placing monitoring wells and pump-and-treat installations, and by finding the optimal control parameters. The objectives typically are to find the minimum cost and the smallest pumping rates and to maximize the reliability.

Meyer and Brill (1988) used linear programming (LP) to solve a location problem of monitoring wells for a remediation case, where the objective function is a weighted function between minimizing the contaminated area and maximizing reliability of the monitoring network. They found a trade-off curve between the two objective functions by solving the problem with different weights. Later Meyer et al. (1994) solved the same problem using the simulated annealing method (SA). In 1995 the problem was solved with EA by Cieniawski et al. (1995), who together with Dougherty and Marryott (1991), Mckinney and Lin (1994) and Marryott et al. (1993) were among the first to use EA to solve groundwater management problems. Marryott et al. (1993) were the first to use EA on a real-world remediation problem, whereas the other studies used theoretical, hypothetical scenarios. Other remediation problems are (Erickson et al., 2002; Mayer et al., 2002; Bayer and Finkel, 2004; Kollat and Reed, 2006; Mantoglou and Kourakos, 2007; Papadopoulou et al., 2007).

Another well studied and applied subject is coastal aquifer management, where the fresh water aquifer is threatened from saltwater intrusion. These problems typically occur in areas with limited drinking water resources and places where abstraction takes place close to the coast. The typical objectives are to abstract a maximum amount of water with a minimum of drawdown and thereby smaller risk of saltwater intrusion (Cheng et al., 2000; Katsifarakis and Petala, 2006; Mantoglou and Papantoniou, 2008).

In many places groundwater is the only source of freshwater supply, and excessive abstraction for irrigation can lead to groundwater depletion. Better management of the groundwater would lead to sustainability of the areas (Sethi et al., 2006; Zheng et al., 2010; Balali et al., 2011). Siegfried and Kinzelbach (2006) used multi-objective genetic algorithms to optimize the management of a shared large aquifer system between three countries. Fowler et al. (2004) and Fowler et al. (2008) solved a water supply problem where they minimize the total cost of supplying water. The total cost is a sum of the drilling cost, transportation cost, abstraction cost, and well maintenance cost.

At smaller scales better groundwater management can improve the operation of a well field - make it more safe, reliable, and cost and energy efficient. The literature contains fewer studies concerning optimization of the operation of well fields than for example remediation problems, but some examples are (Ahlfeld and Mulligan, 2000; Ahlfeld and Baro-Montes, 2008; Tsai et al., 2009; Bauser et al., 2010). The energy consumption of a waterworks is considerable and Madsen et al. (2009) and Refsgaard et al. (2009a) investigated energy optimization of well fields.

Water distribution networks are also a well studied field, and research has been performed in both designing distribution networks and in optimal pump scheduling (Simpson et al., 1994; Ormsbee and Lansey, 1994; van Zyl et al., 2004; Farmani et al., 2005; Tu et al., 2005; Tsai et al., 2009). Rao and Salomons (2007) provided an interesting study, where a neural network model is used to find the optimal pumping schedule of a hypothetic water distribution network. The neural network model is used to speed up the calculation time, which makes it possible to develop a real-time operation approach using EA.

A numerical groundwater model is typically not sufficient to get a reliable energy consumption estimate of the well field. The total energy consumption consists of the energy required to lift the water from the aquifer to the surface and the energy required to run the pumps. In the literature is typically described a) the pipe network, and the aquifer is then treated as a reservoir with a given groundwater head, or b) the groundwater system, and pipe hydraulics and energy loss in pumps are being ignored or simplified. Two exceptions are Pezeshk et al. (1994), who optimized the total delivery cost of the well field and the distribution system and Tsai et al. (2009), who created a one-way coupling between a pipe network model and a groundwater model, so that the pipe network model provides average pumping rate to the groundwater model, which is then used to calculate the drawdown. In addition Madsen et al. (2009) and Refsgaard et al. (2009a) used a fully dynamic coupling between the groundwater model and the pipe network model. The model is called WELLfield Numerical Engine Shell model (WELLNES) (Falk and Madsen, 2011), which is used in this research.

2.2 Optimization methods applied in groundwater management

Working with groundwater management is a challenge, because of its highly non-linear and complex nature. With the use of purely deterministic search methods it can be difficult or impossible to solve groundwater optimization problems.

EA have proven to be a valuable tool in groundwater optimization, and the use of EA has steadily increased since the first use in the nineties. EA is a heuristic method that does not depend on derivatives, but only depends on the evaluation of the objective function. This makes it possible to solve discrete and highly non-linear problems. The basic principle behind EA has not changed since the first use, but the tools have been refined over time to become more and more effective in terms of the search procedures and speed.

The major difference between EA and other optimization algorithms is that EA works with a population of individuals that evolves in generations, where other techniques only improve one individual at the time.

An EA consists of three parts:

1. Evaluation of the objective function values (including model simulations)
2. A recombination of individuals, consisting of crossover and mutation.
3. A selector, which selects the individuals that reproduce in the next generation.

Number 1 and 2 depend on the problem and will be discussed in section 3 and section 4. Number 3, the choice of selection operator, is important and can in worst case lead to premature convergence or stalling of the optimization, otherwise it affects how fast the optimization is converging to the Pareto front (Nicklow et al., 2010). The selection operator has two purposes. First, to find the non-dominated individuals in the population. Second, to find a set of individuals that is as diverse as possible (Deb, 2001). Genetic algorithms (GA) is a subclass of EA.

Among the first uses of EA was the Boltzmann selection, using the same principles as the simulated annealing method (Dougherty and Marryott, 1991). Simulated annealing and EA are both heuristic methods, and simulated annealing was one of the first methods used on groundwater problems. Simulated annealing progresses by creating small displacements in the decision space. If the new objective function value has improved, it is accepted, if not, it is accepted with a given probability. This gives the algorithm a chance of escaping a local optimum. Dougherty and Marryott (1991) used SA to optimize a remediation design using a hypothetical scenario, and Marryott et al. (1993) used it as one of the first on a real-world remediation problem. Simulated annealing has been illustrated to work with success in a number of applications, also in recent studies (Shieh and Peralta, 2005).

Roulette wheel selection was used in the beginning of EA history, but today it is not recommended, because it can drift or stall in late generations if the individuals have similar fitness values, or premature convergence can occur if one single super-solution exists (Nicklow et al., 2010). The selection procedure lacks the elitist property, which has shown to be important for the effectiveness of EA (Bayer and Finkel, 2004; Yoon and Shoemaker, 2001).

Elitist selection operators ensure the survival of the best individuals and the most popular ones today are the Nondominated Sorting Genetic Algorithm Il (NSGA-II) (Deb et al., 2002), the improved version ϵ-Nondominated Sorting Genetic Algorithm Il (ϵ-NSGA-II) (Laumanns et al., 2002), and the Strength Pareto Evolutionary Algorithm 2 (SPEA 2) (Zitzler and Thiele, 1999; Zitzler et al., 2002).

The NSGA-II and ϵ-NSGA-II both perform a crowded binary tournament between individuals based on their fitness value. The fitness assignment is based on their rank (number of individuals it dominates). ϵ-NSGA-II adds the parameter, ϵ, which determines the density of the Pareto front. A small ϵ value leads to a dense Pareto front, while a large ϵ value lead to a sparser, but well distributed, Pareto front. ϵ-NSGA-II introduces a dynamic pool size, which changes dependent on the number of individuals it dominates, and it terminates itself when the solutions have not increased by a certain percentage in two successive generations.

The fitness assignment of SPEA2 is based on both the number of individuals each individual dominates and on the density information (how close the individuals are in objective space). The pool size is fixed, and in each generation all non-dominated individuals are transferred to the pool. Two scenarios exist. If the number of non-dominate individuals is smaller than the pool size, the pool is filled with the best dominated solutions. If the number of non-dominated individuals is larger than the pool size, an archive truncation algorithm removes the individuals with the smallest crowding distance. The crowding distance is a measure of the distance to the closest individuals in the objective space.

Of the three selectors mentioned here, SPEA2 and ϵ-NSGA-II perform equally well, and both outperform the NSGA-II. The key difference between the ϵ-NSGA-II and SPEA2 is that ϵ-NSGA-II has fewer algorithmic parameters to be tuned and thus is more user-friendly (Nicklow et al., 2010; Kollat and Reed, 2006).

Several methods to solve groundwater management problems exist. LP (Ahlfeld and Mulligan, 2000) is very useful for simple groundwater management problems that can be considered linear and continuous. The main drawback of this method is that all objective functions and constraints must be linear.

Sampling methods, e.g. the implicit filtering method, use a derivative-free algorithm (Fowler et al., 2004, 2008). It uses model evaluation in a mesh around the point to estimate the gradient of the objective function, and uses either a traditional gradient method or a quadratic surrogate model of the objective function to perform the iteration step of the model. If a better value is found the step is taken, if not the size of the mesh is reduced during the next iteration. This method works in non-linear problems, but the problem has to be smooth and with a small noise level. Fowler et al. (2004) and Fowler et al. (2008) have used implicit filtering with success on a hypothetic well field design problem. They have also compared the performance with EA and found the implicit filtering less robust than EA but faster.

Other possibilities for optimizing groundwater management are for example stochastic methods (Mantoglou and Kourakos, 2007) or optimal hierarchical control (Park et al., 2007; Bauser et al., 2010). The latter is useful for real-time operation. Besides the methods mentioned here a number of combinations of different methods exist (Mayer et al., 2002; van Zyl et al., 2004; Tu et al., 2005; Rao and Salomons, 2007; Mantoglou and Papantoniou, 2008).

EA are a valuable tool in groundwater management. The main advantage is that EA does not require derivative information like others of the mentioned methods, and it is capable of solving complex non-linear problems. Another advantage is its ability to handle multi-objective function optimization problems, and it can find solutions to non-convex and discrete problems. The other methods mentioned here work with one objective function, which in case of more objectives are aggregated into one objective function with weighted superposition. By varying the weight, the trade-off curve between the conflicting objective functions can be found (the Pareto front). If the problem is convex, the Pareto front cannot be found due to the linear combination of the different objective functions. If the optimal point on the front does not change over a wide range of weighting factors values, this can also lead to problems for the aggregated objective functions methods (Cieniawski et al., 1995).

EA does not guarantee the true optimal solution. However, it has the ability to rapidly steer the population towards the Pareto front, and also near-optimum solutions can be useful in groundwater management. The main drawback of EA is that it requires many model evaluations to get the solution to converge. Especially in real-world groundwater optimization problems this is a challenge, because of CPU intensive numerical models. However, the performance of computers is steadily increasing, and EA are well suited for parallelization. Most likely this is also the reason why we have seen an increased numbers of papers using EA on groundwater management in the last decade.

Cunha (2002), Mayer et al. (2002), and Nicklow et al. (2010) all present reviews of different optimization methods applied in groundwater management.

3 Case studies

In this chapter the two case studies are presented. Section 3.1 introduces Hardhof waterworks and Section 3.2 introduces Søndersø waterworks. The two waterworks abstract approximately the same amount of water, but are in other ways very different.

3.1 Case 1: Hardhof waterworks

The drinking water supply for the city of Zurich consists of 15% groundwater abstracted from Hardhof well field, 70% lake water taken from the two lake waterworks Lengg and Moos and 15% spring water from Sihlbrugg spring waterworks. This case study focuses on improving the management of Hardhof ground waterworks. The waterworks is located next to the river Limmat close to the city center of Zurich and is surrounded by industrial, potentially contaminated, sites (Figure 3.1). The groundwater aquifer consists mainly of sandy gravel and moraine material. A more detailed description of the area and the groundwater model used in the optimization is given in Doppler et al. (2007) and Hendricks Franssen et al. (2011). The waterworks abstracts water (20,000 m^3/day) from 4 large horizontal wells located within an area of 1 km^2 . The aquifer below the well field is artificially recharged by bank filtrated river water through 12 injection wells and three infiltration basins. This serves multiple purposes:

1. It allows to abstract 20,000 m^3/day from the aquifer without large drawdown.
2. The water residence time in the aquifer is increased to improve the water quality and to reduce the risk of microbiological pollution.
3. The infiltrated water creates a barrier towards the industrial sites, which avoids intrusion of potentially contaminated water into the production wells.

The aim of the case study is to optimize the pumping- and infiltration rates, with respect to the objectives of minimizing the amount of water needed for the infiltration (I_{total}) and minimizing the risk of getting contaminated water into the production wells. The latter is quantified in the parameter H, which is the minimum value of the head differences between the three pairs of head observation wells, shown in Figure 3.1. The waterworks has to fulfil a certain demand of water (Q_{dem}). A formal description of the optimization problem is given in Paper I.

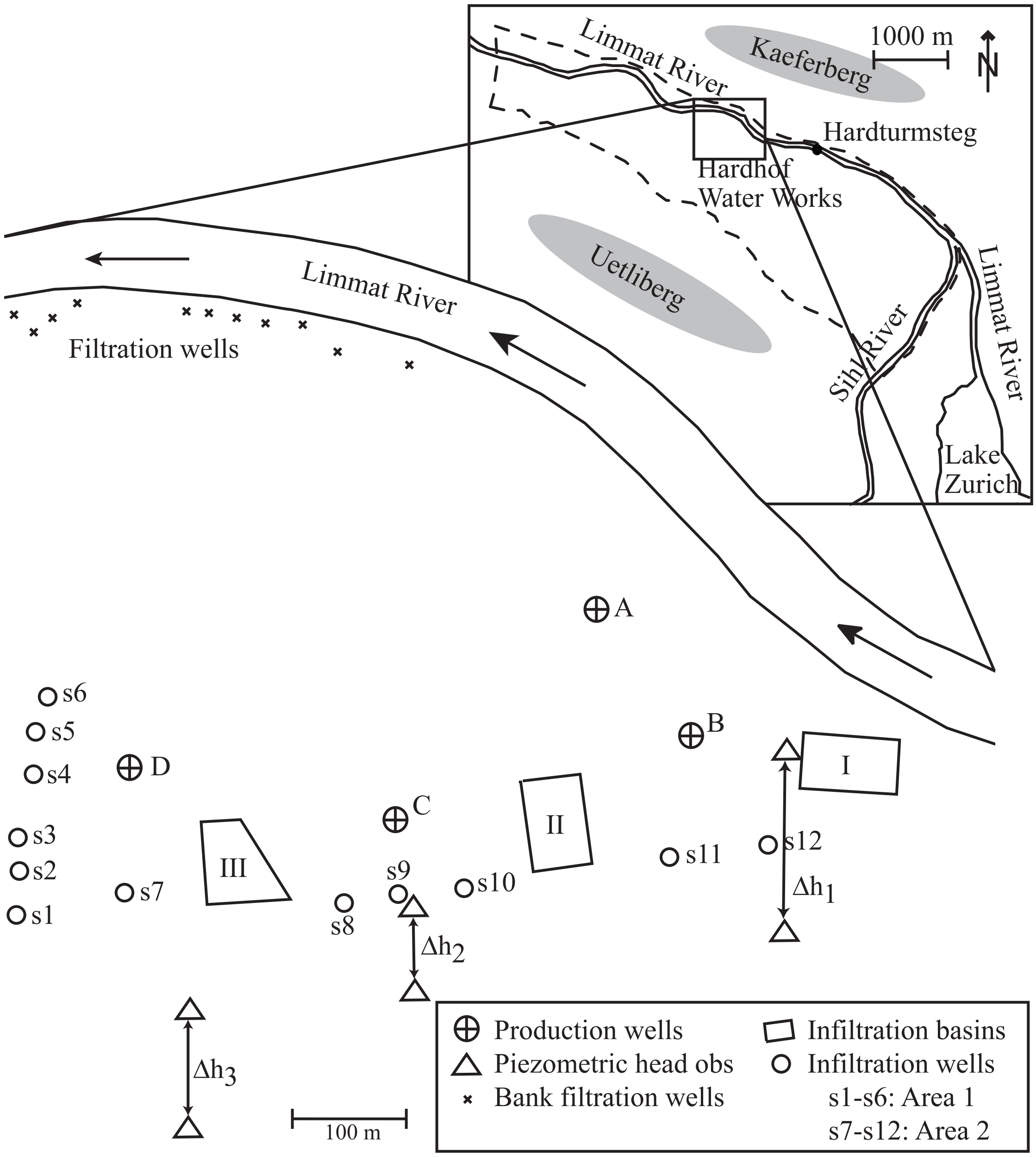

Figure 3.1: Sketch of the Hardhof well field. The dashed line shows the model area.

3.1.1 Data and model

Abstraction, infiltration, and hydrological data exist for 1.5 years (01.01.2004 to 31.08.2005). The groundwater model by Doppler et al. (2007) is used. Two subperiods with different characteristics have been selected for use in the optimization. The first period (30.12.2004-31.01.2005) is a dry period with constant hydrological conditions and with fairly constant pumping and infiltration rates. On average 20,600 m^3/day of water is abstracted, and 1.4 times the abstracted amount of water ($I_{total,dry} = 29,199$ m^3/day) is infiltrated (Figure 3.2).

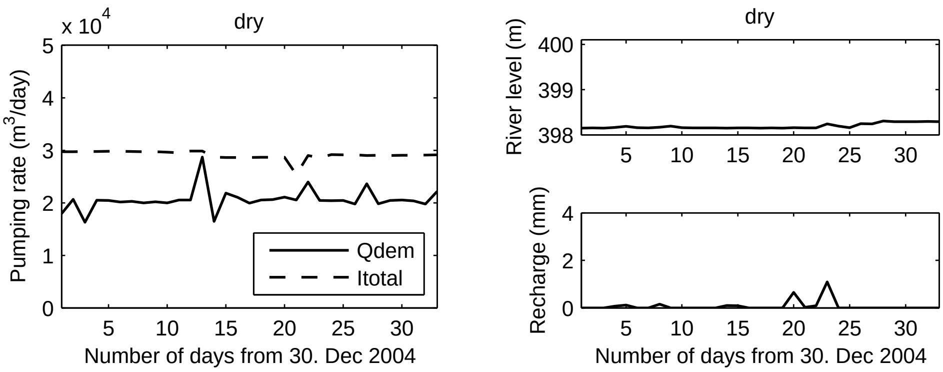

Figure 3.2: Historical values for the dry period (30.12.2004-31.01.2005). Left: Total abstraction which is also the demand (Q_{dem}), and infiltration (I_{total}). Right top: Observed river levels at the Hardturmsteg, located just upstream of the Hardhof water works (see Figure 3.1). Right bottom: Estimated recharge to the aquifer (Doppler et al., 2007).

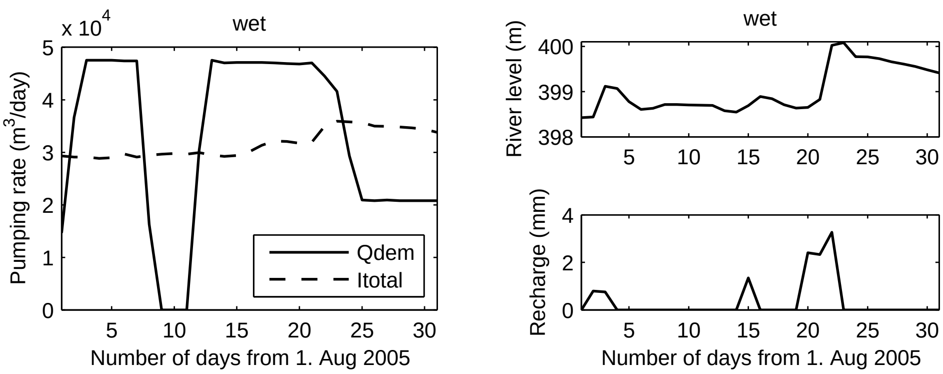

Figure 3.3: As for Figure 3.2, but for the wet period (1-31.08.2005).

The second period (1.08.2005-31.08.2005) is a wet period with variable pumping, infiltration, and hydrological conditions. The river level of Limmat is high and at the end of the period the water level rises 1.5 m due to a flood event. In average 32,900 m^3/day is abstracted and the amount of infiltration is almost the same ($I_{total,wet} = 31,600$ m^3/day) (Figure 3.3).

3.2 Case 2: Søndersø waterworks

Søndersø waterworks is located northwest of Copenhagen (Figure 3.4) and abstracts approximately 20,000 m^3/day of water from 21 wells distributed over 3 well fields, Tibberup well field (10 siphon pumps), Søndersø West (3 submersible pumps), and Søndersø East (8 submersible pumps). The prime interest in this research is the operation of the submersible pumps.

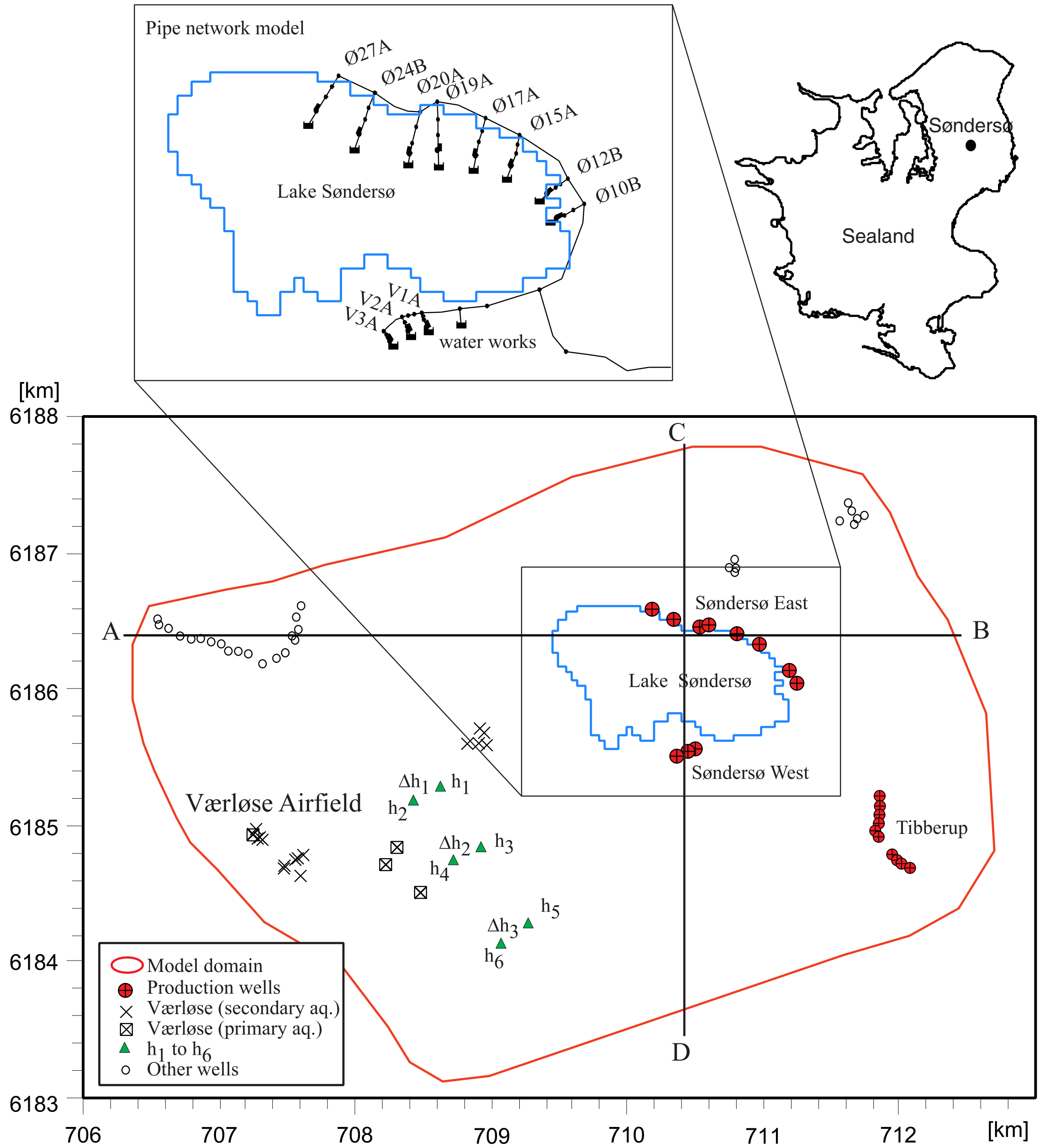

Figure 3.4: Model domain showing location of the production wells, the protective wells at Værløse airfield. h_1 to h_6 are points which are placed in the groundwater model along the water divide. Figures of cross sections along the lines AB and CD are shown in Paper I.

Værløse Airfield, which was closed in 2004, is located west of the waterworks. The area is contaminated with chlorinated hydrocarbon compounds and 20 protective wells are installed. Four of them abstract water from the primary aquifer, the rest from the secondary aquifer. The abstracted water is treated and released into the local stream.

The primary aquifer consist of Tertiary Danian limestone and has a thickness of approximately 25 m. Above the limestone is 40-60 m of Quaternary clay and sand deposits, rising to 80 m in the northernmost part of the area. All wells except Ø20A are screened in the limestone. Well Ø20A is screened in a larger secondary sand layer. Figures of the cross sections along the lines Ab and CD in Figure 3.4 are shown in Paper I (Figure 3 and 4).

The aim of the case study is to optimize the pumping configuration of the waterworks with respect to the objectives of minimizing the specific energy (E_{spe}) and minimizing the risk of getting contaminated water from Værløse Airfield into the production wells (H). H is the average of the head difference Δh_1, Δh_2, and Δh_3 shown in Figure 3.4, where for example $\Delta h_1 = h_1 - h_2$. h_i are points which are placed along the water divide in the model and they provide head values. A positive Δh_i value indicates a flow towards the airfield, and a negative Δh_i value indicates a flow towards the well field. It is desired to have positive values. The waterworks has to provide a certain demand of water, Q_{dem}.

It is investigated to which extent the objectives are improved, if new variable-speed pumps are installed in all wells compared to the existing on/off wells. A formal description of the optimization problem are given in Paper I for the on/off pumps, and in Paper II for the variable-speed pumps.

3.2.1 Data and model

An extensive measurement campaign at Søndersø waterworks was performed in the period 03.11.2008 to 01.09.2009, where head elevation, pumping rates, and energy consumption of each well were measured every minute. According to the pump data pumps are on in average 80% of the time. The data are used to calibrate the WELLNES model (section 3.2.3). From Værløse Airfield climate data and abstracted water amounts (monthly averaged) for 10 years exist (2000-2009). A regional model provides boundary conditions for the local model. Two periods are selected to be used in the optimization. During the the first period (03-10.11.2008) abstraction is 59% of the waterworks maximum capacity of 735 m^3/hour. During the second period (03.-10.03.2009) abstraction is 86% of the maximum capacity.

3.2.2 Pump types

The pump types play an important role in the optimization of Søndersø waterworks. The pumps installed at Søndersø waterworks are on/off pumps that can operate at one speed only. Pump curves represent a unique relation between power,

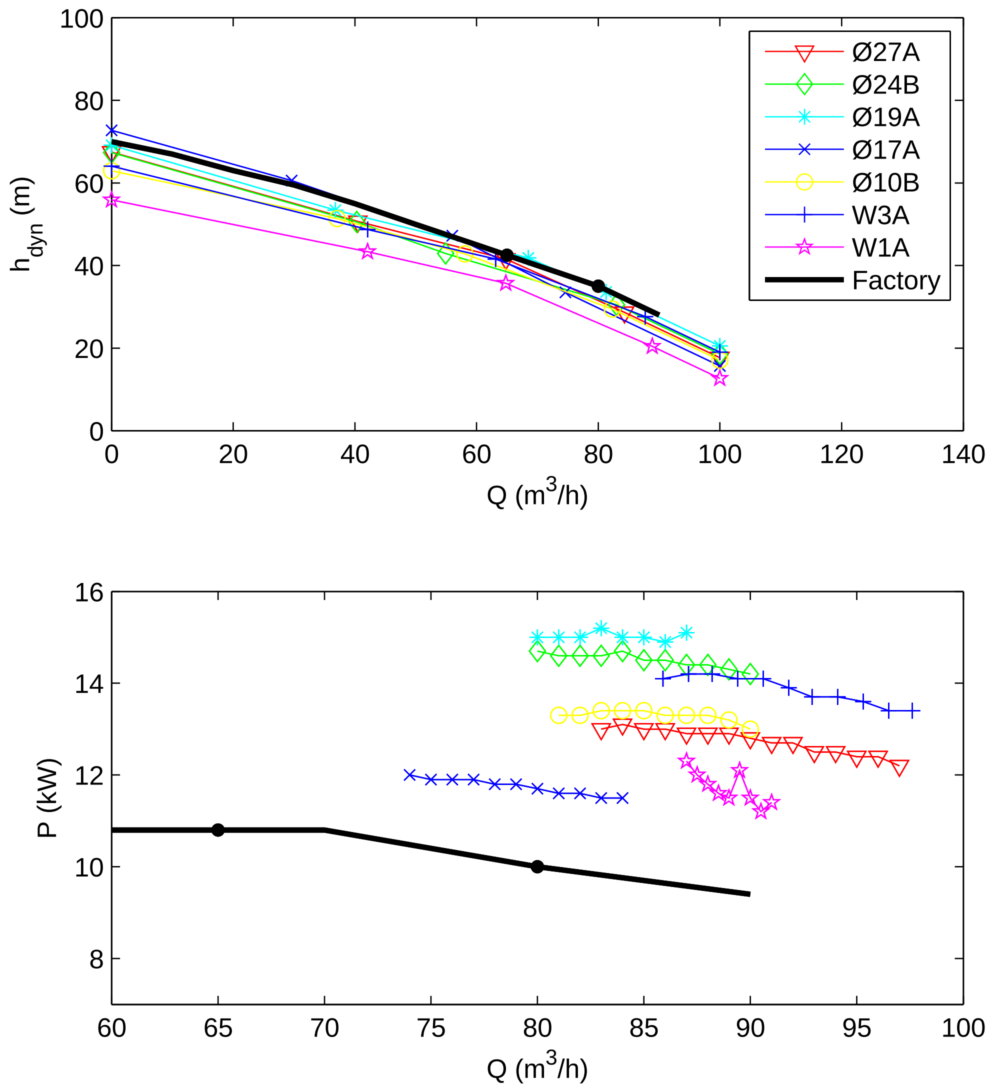

Figure 3.5: Effective pump curves for the SP75-4 pump located in 7 wells. Top: The dynamic head h_{dyn} as function of the pumping rate, Q. Bottom Power P as function of the pumping rate.

pumping rate and dynamic head ($P - Q - h_{dyn}$-curves). These curves are a property of the pumps and are provided by the manufacturer. Over time the pump curves change due to wear and clogging of the pump, and effective pump curves must be obtained by measurements. Seven pumps at Søndersø waterworks are the same type (SP75-4), and their effective pump curves together with the manufacturer pump curve can be seen in Figure 3.5.

When a variable-speed pump is installed, the speed of the pump can be varied within a certain interval, typically 0.6 to 1, where 1 is maximum speed. A pump running with speed 1, has the same pump curve as an on/off pump of same type (except for some energy loss in the engine). When reducing the speed, the pump curve will change according to the affinity laws. The relationship between P, Q and h_{dyn} for two different speed values (s_1 and s_2) are:

$$\frac{Q_1}{Q_2} = \frac{s_1}{s_2}, \qquad \frac{h_{dyn1}}{h_{dyn2}} = \left(\frac{s_1}{s_2}\right)^2, \qquad \frac{P_1}{P_2} = \left(\frac{s_1}{s_2}\right)^3, \qquad \frac{\eta_1}{\eta_2} = 1, \tag{3.1}$$

where η is the efficiency of the pump.

In this research we investigate two different variable-speed pump alternatives, A1 and A2, that can be seen in Table 3.1. For $s = 1$ the pump curves of these pumps are shown in Figure 3.6. Note how the curves for different stages of same pump type have similar shape but different level. Figure 3.7 shows how the pump curve for the SP95-4 pump will change according to different speed values.

3.2.3 WELLNES

The WELLNES model is a coupled simulator using a groundwater model (Graham and Butts, 2006), a pipe network model (Rossman, 2000), and a well model (Halford and Hanson, 2002). It simulates the hydrological and hydraulic state variables in and around a well field, and especially it simulates the dynamic head in the production wells. The latter is important when calculating the energy consumption of the pumps. For a detailed description of WELLNES the reader is referred to Paper II or Falk and Madsen (2011).

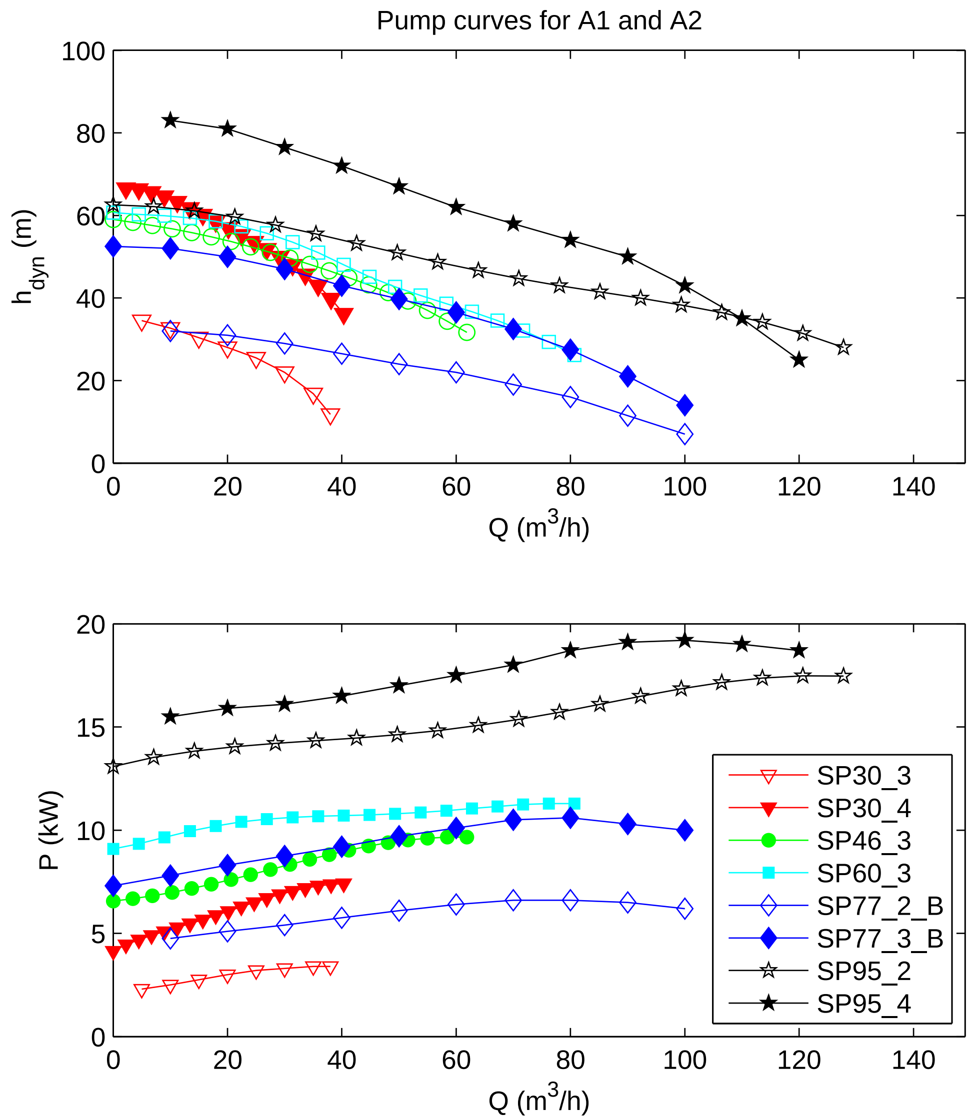

Figure 3.6: Factory pump curves for the pumps used in A1 and A2. See Table 3.1. The number after the pump name, for example "-2" in SP95-2, defines the number of stages the pump has. The more stages the more powerful is the pump.

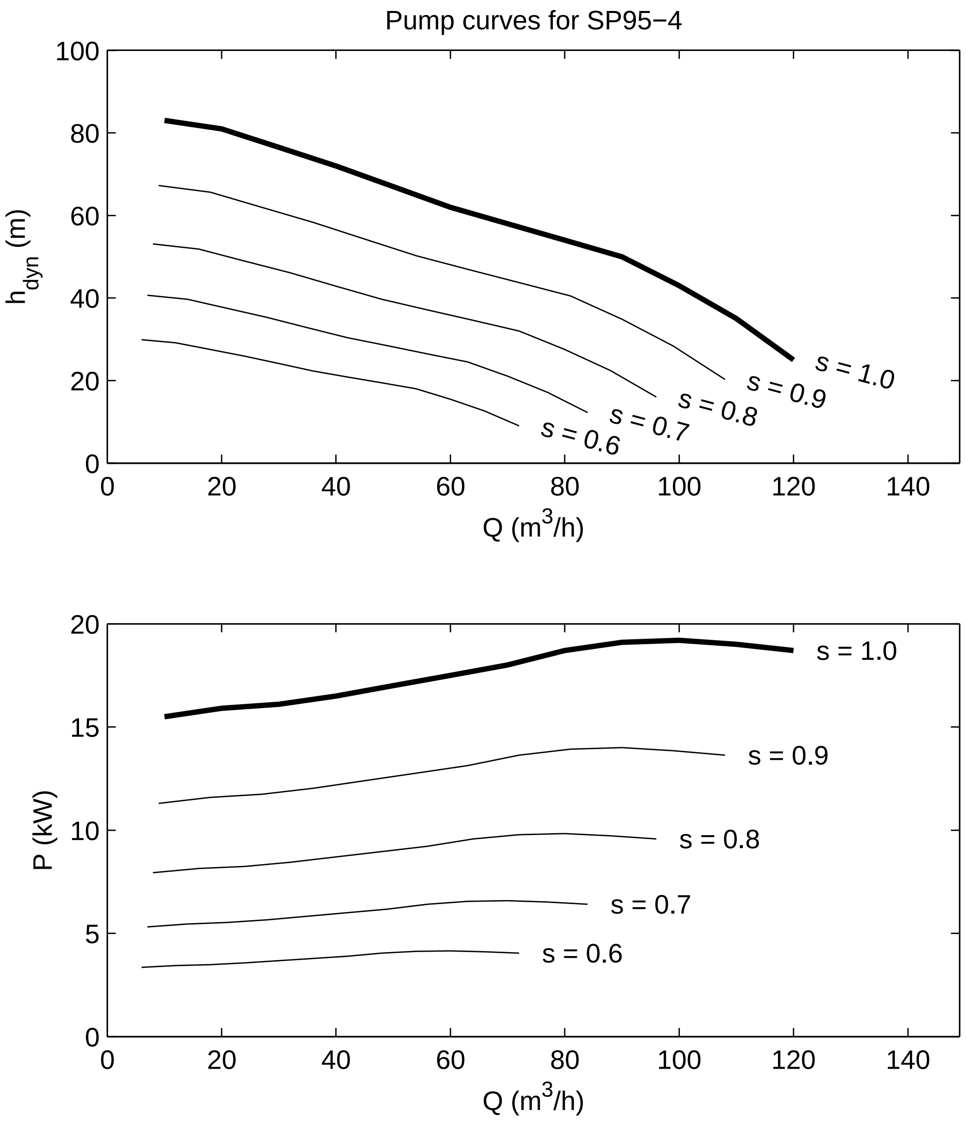

Figure 3.7: Pump curves for SP95-4; shows how Q, h_{dyn}, and P changes when the speed, s, changes from maximal speed ($s = 1$) to minimum speed ($s = 0.6$). Typically the speed can not be lower than 0.6. In this case the pump is switch off.

Table 3.1: Pump types for three different pump setups for the waterworks. The location of the wells can be seen in Figure 3.4. Pumps marked with * are on/off pumps, all others are variable-speed pumps. All the pumps are from the company Grundfos, and details of the different pump types can be found at Grundfos WebCAPS at www.grundfos.com.

s_i	Well name	Present pumps	A1	A2
s_1	Ø27A	SP75-4*	SP77-3B	SP95-4
s_2	Ø24A	SP75-4*	SP77-3B	SP95-4
s_3	Ø20A	SP27-5*	SP46-3	SP30-3
s_4	Ø19A	SP75-4*	SP77-3B	SP95-4
s_5	Ø17A	SP75-4*	SP77-3B	SP95-4
s_6	Ø15A	SP27-5*	SP30-4	SP27-5
s_7	Ø12B	SP45-4*	SP60-3	SP95-4
s_8	Ø10B	SP75-4*	SP77-3B	SP95-4
s_9	V3A	SP75-4*	SP77-3B	SP77-2-B
s_{10}	V2A	SP60-3*	SP60-3	SP77-2-B
s_{11}	V1A	SP75-4*	SP95-2	SP77-2-B

4 Methods

The groundwater management problems considered in this research are solved by GA, which have the prime advantage that they can solve almost any kind of optimization problems, no matter if the problem is linear or non-linear, convex or non-convex, continuous or discrete, single-objective or multi-objectives. In section 4.1 the principle of GA is described. Two different optimization methods are considered and are presented in section 4.2. Finally section 4.3 briefly describes the recombination and selection procedure.

4.1 Genetic algorithms

GA is a heuristic method that uses Darwin's principle of "Survival of the fittest" to find a set of non-dominated solutions, where none of the solutions can be said to be better than any of the others.

A GA works with a population of individuals, where an individual is a combination of possible values for all decision variables. The principle behind a GA is simple and a diagram of the algorithm can be seen in Figure 4.1. The algorithm starts by creating an initial population of individuals. The groundwater model is simulated once for each individual and the objective function values are calculated. The selection module selects, based on the objective function values, the best individuals of the population. These individuals are then recombined by crossover and mutation. The objective function values are calculated for the new population and the best individuals are selected. The algorithm continues until a maximum number of generations is reached and the optimization has converged to a set of optimal non-dominated solutions. The convergence performance of the GA can be tested by using the hypervolume identification (Knowles et al., 2006).

4.2 Optimization methods

Section 4.2.1 describes the constant scheduling optimization used at the Hardhof and Søndersø waterworks cases (Paper I, II, and III), where all decision variables are held constant during the optimization period.

Section 4.2.2 describes the sequential scheduling optimization, used at the Hardhof waterworks case (Paper I), where optimization is performed for a shorter time step at a time. This allows the pumping configuration to vary in time, and is a real-time approach.

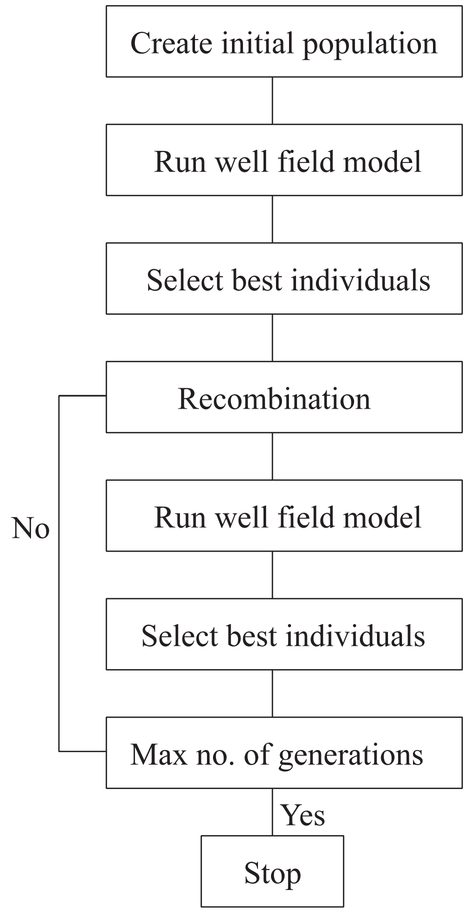

Figure 4.1: Sketch of the GA.

Section 4.2.3 describes a constant scheduling optimization used on Søndersø waterworks (Paper II and III). Here the decision variables (the pump status) are changed from a binary to a real-value representation. It is investigated how a new set of variable-speed pumps will improve the management compared with the on/off pumps.

4.2.1 Constant scheduling

In constant scheduling optimization the decision variables are kept constant in the evaluation period. The constraint is at both Hardhof and Søndersø waterworks the demand of water, given as the average of the simulated historical amount of abstracted water in the same period. The result of the optimization is the Pareto front from which the decision-makers can choose a solution to implement at the waterworks. The decision-makers can make their choice based on the objective function values and higher-level information.

4.2.2 Sequential scheduling

In sequential scheduling the optimization is performed for a shorter time period, for example one day at a time. Higher-level information is used to choose a solution on the Pareto front and the solution is implemented for the given period. The same optimization procedure is performed for the next time steps. Each time step provides **one** Pareto front, from which **one** solution is chosen. In this way the decision variables can change at every time step, adapting to the varying hydrological conditions. The water demand is given as the average of the simulated historical amount of abstracted water for the given time step. Sequential scheduling has the ability to be implemented in a real-time application, since only the input to the hydrological model and the demand have to be known one time step ahead.

4.2.3 Constant scheduling: Changing decision variables

The last type of optimization performed in this research considers different types of decision variables. The pump types in Paper II can be either on or off, thus it is natural to represent these decision variables as a binary string. In Paper III, it is investigated what happens if the pumps are changed to newer variable-speed pumps. In this case the decision variables are represented with real value coding.

4.3 Recombination and Selection

The recombination consists of crossover and mutation operators. See Papers I, II, and III for detailed descriptions of the different crossover and mutation operators. The principle of the crossover operator is to use the existing solutions to create better solutions, whereas the mutation operators modifies good individuals to get new genes into the algorithm to test unexploited areas of the decision space.

The selection of the "good" individuals that survive to the next generation is in the case of multiple objectives not a trivial task. Here we use the elitist SPEA2 algorithm. The software PISA developed at ETH Zurich, Switzerland (Bleuler et al., 2003) is used for implementing SPEA2. The PISA software couples the problem dependent part (model evaluation, recombination) together with the problem independent part (selection). The only exchange of information is the individuals objective functions values and ID's of the individuals, which is implemented through text files. PISA provides different ready-to-use selection modules. For details of the selection, see Papers I, II, and III.

5 Results and discussion

The general results of this study show that groundwater management can be greatly improved by applying multi-objective optimization. In all cases both objective function values are improved compared with the historical management. Furthermore, the Pareto fronts provide the decision-makers with different management alternatives.

The results from the Hardhof case study are presented in section 5.1, and the results from the Søndersø case study in section 5.2.

5.1 Hardhof waterworks

The optimization for Hardhof waterworks was performed for a dry and a wet period. Figure 5.1 shows the Pareto front for the constant scheduling for the two periods. The crosses shows the solutions on the Pareto front and the dots are all the possible solutions that have been evaluated during the optimization. The model is simulated with the historical data and the objective functions values for this solution is the solid diamond.

For both periods it is possible to improve the management with respect to the two objective functions compared to the simulated historical management. The total infiltration for the historical operation was approximately 30,000 m^3/day for both periods, and H was -1.7 cm for the dry period and -6.7 cm for the wet period. Both H-values are negative constituting a risk of getting flow of contaminated water towards the well field. The potential improvements are highest in the wet period, where it is possible to improve H by 4.5 cm if the infiltration is kept constant (circles in Figure 5.1). It is however not possible to obtain positive H values during the wet period. For the dry period positive H values can be obtained by increasing the infiltration with 20%.

The sequential scheduling was also performed for the two periods. At each time step a solution was chosen, based on higher-order information. Here we chose to improve H while keeping the infiltration I_{total} at the same level as the historical operation. The average of the objective function values are showed as the triangles in Figure 5.1. From this it is seen that the performance of the constant and sequential scheduling are almost the same.

Figure 5.2 shows the management of the optimal solutions for constant scheduling, sequential scheduling and simulated history. Figure a) and d) show the total

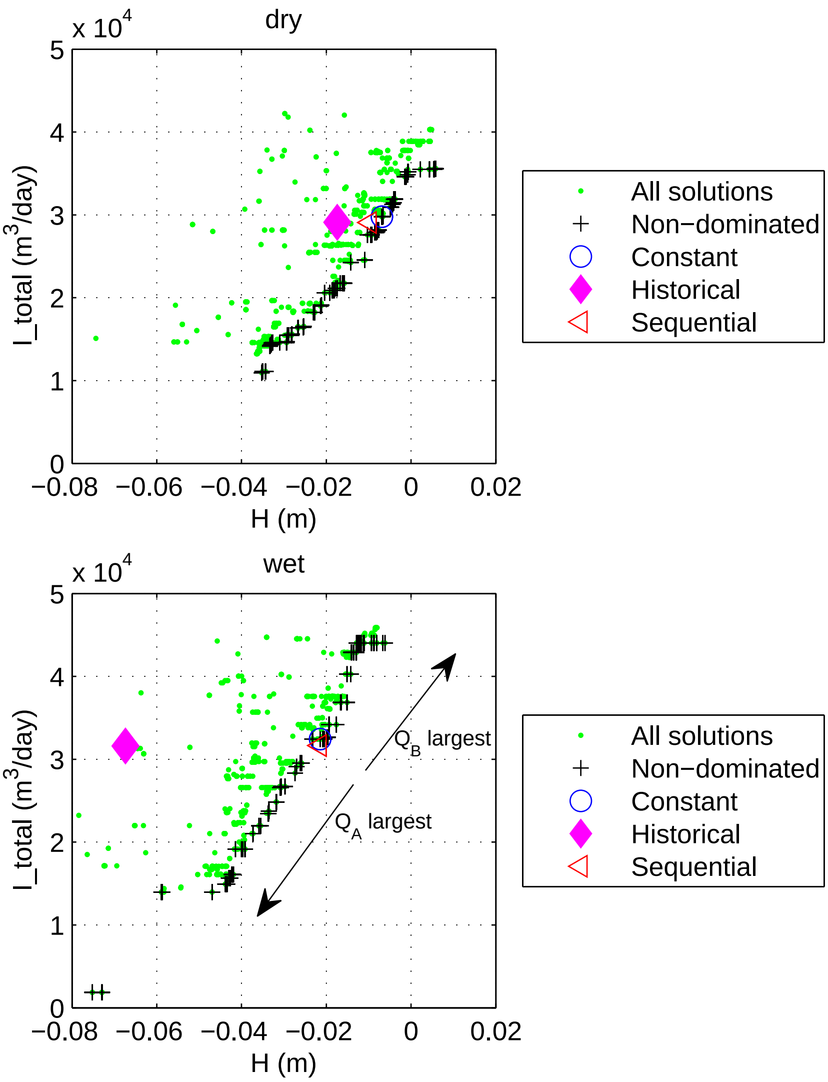

Figure 5.1: Pareto front for constant scheduling for the dry and wet period. See text for explanation. The arrows labeled Q_A and Q_B indicates a shift in the Pareto optimal solutions. From solutions where the largest abstraction happens from Q_A to solutions where largest abstraction happens from Q_B.

infiltration to the basins, Figure b) and c) show the total infiltration to the wells, and Figure c) and f) show the objective function H. The objective function I_{total} is constant in the period.

All optimization runs find that more water should be infiltrated in the basins and less in the wells. In the dry period, constant scheduling outperforms sequential scheduling which varies from day to day between a good solution and a less good solution. In the wet period, sequential scheduling outperforms constant scheduling during the extreme events at day 6 to 11 and day 20 to 30.

Paper I shows how the optimized solution for constant scheduling and sequential scheduling change the distribution of the infiltration and abstraction compared with the historical distribution. Further is given a comprehensive comparison with the study by Bauser et al. (2010), as well as a discussion of the definition of H.

The differences between the two optimization methods are:

1. Constant scheduling requires information about water demands and the hydrological forcings for the entire simulation period. Sequential scheduling requires only information about the next time step.
2. Constant scheduling has less degrees of freedom than sequential scheduling.
3. Optimizing in real-time operation is possible with sequential scheduling. With constant scheduling it is not possible.

The optimized management is therefore a balance between required forecast information and degrees of freedom.

A suggestion for future work that uses the best part of both constant scheduling and sequential scheduling is to perform sequential scheduling with longer subperiods, for example 5 days, but still only implement the first day of the management solution. This would give less variability in the final management solution, but still keep the strength of sequential scheduling as it does not require information about the whole optimization period. However, this optimization method will be more CPU intensive.

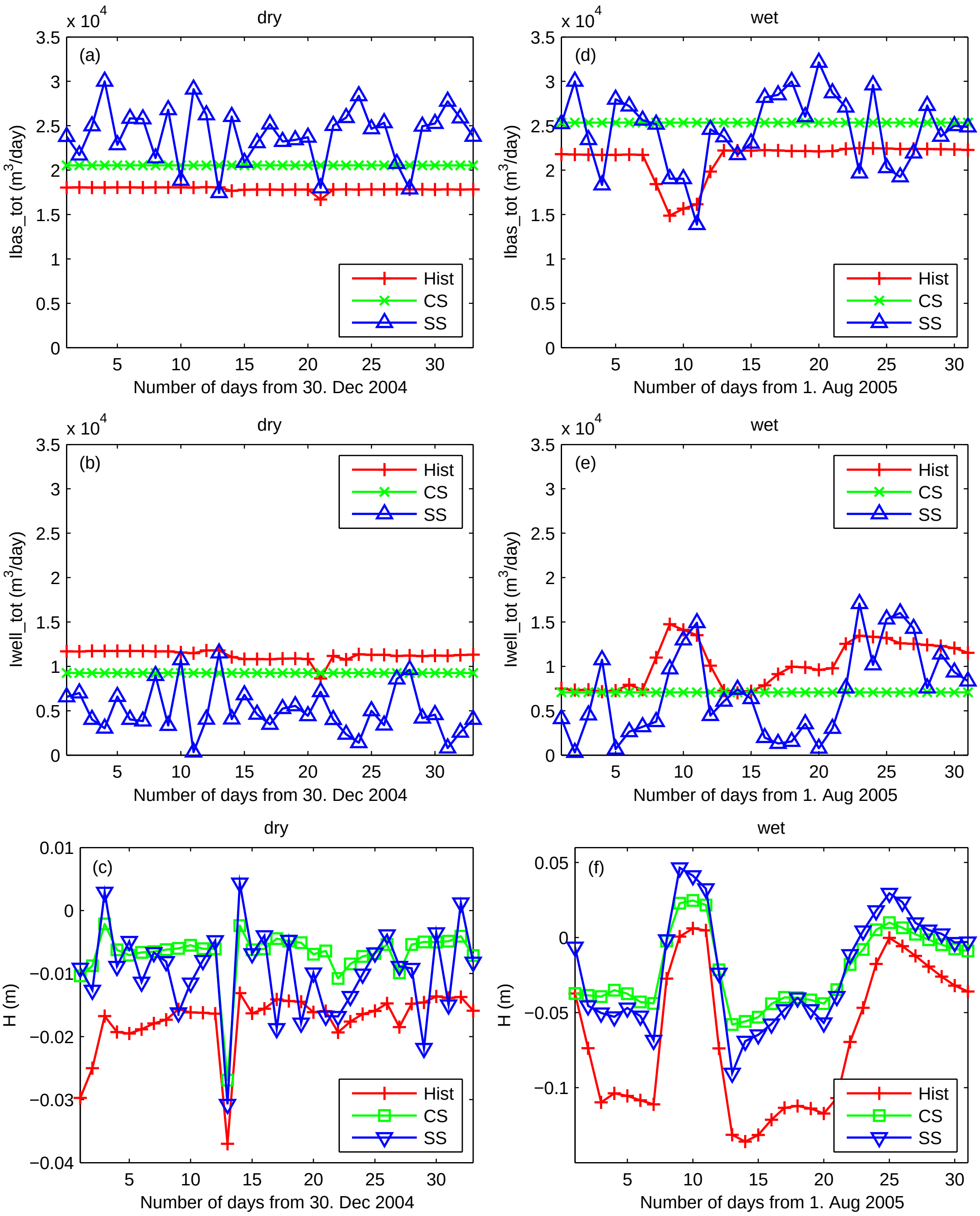

Figure 5.2: Each sub figure shows the historical simulation (Hist), the constant scheduling (CS) and the sequential scheduling (SS). (a) Total infiltration to basins, $Ibas_{tot}$ (dry). (b) Total injection to the wells, $Iwell_{tot}$ (dry). (c) The objective function H (dry). (d) Total infiltration to basins, $Ibas_{tot}$ (wet). (e) Total injection to the wells, $Iwell_{tot}$ (wet). (f) The objective function H (wet). Remark that the scale of the y-axis in figure c is smaller than the scale in figure f. For further details see Paper I.

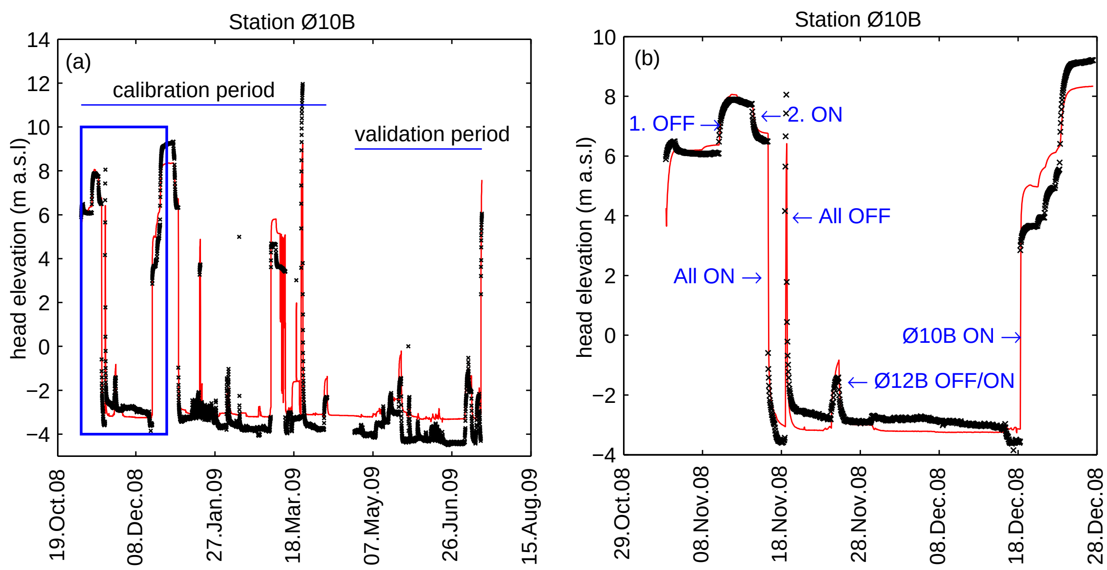

Figure 5.3: (a) Observation (crosses) and simulation (solid line) of head elevation in well Ø10B in both calibration and validation period. (b) Enlargement of the rectangle in the figure a). The text written in the figure refers to the historical pump operations. 1. OFF means: Ø15A, Ø17A, and Ø20A OFF. 2. ON means: Ø17A and Ø20A ON.

5.2 Søndersø waterworks

This section will first present the performance of the WELLNES model (section 5.2.1) followed by the results of the optimization (section 5.2.2).

5.2.1 Performance of WELLNES

The WELLNES model was set up for the Søndersø area and calibrated for a period of 5 month. A period of 3 month was used for validation. Figure 5.3.a shows the simulated and observed head elevation for well Ø10B for both the calibration and validation period. The WELLNES model captures the aquifer's rapid response when pump speeds are changed. Figure 5.3.b is an enlargement of the box in figure a) and shows that the head elevation in the well is sensitive to the neighboring pumps turning on or off. Figure 5.4 shows the prediction of the total power consumption. Also here the correspondence between observed and simulated power is good.

Table 5.1 shows the overall performance of the model for the calibration period. It shows that the model predicts 3.8% less total abstraction than observed and that it predicts 0.7% larger energy consumption than observed.

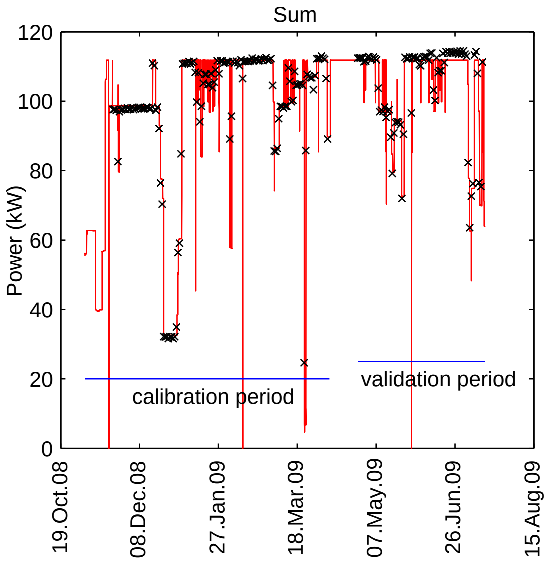

Figure 5.4: Observation (crosses) and simulation (solid line) of the total power consumption for Søndersø east and west in both calibration and validation period.

Table 5.1: Performance of WELLNES for Søndersø Øst and West in the calibration period.

	Total abstraction	Total energy
Observed	2,420,260 m^3	321,991 kWh
Simulated	2,329,487 m^3	324,266 kWh
Simulated-Observed, absolute	-90,773 m^3	2,275 kWh
Simulated-Observed, relative	-3.8%	0.7%

The error on the energy consumption is smaller than the error on the abstraction. This is because of the properties of the pump curves, where the $P - Q$ curves are flat in the operation interval. An error in the pump rate will give a smaller error in the power consumption.

5.2.2 Optimization of management

The multi-objective optimization (constant scheduling) was performed for a low ($Q_{dem,L}$) and a high ($Q_{dem,H}$) demand period. The optimization was performed for the present on/off pumps at Søndersø and for two different pump alternatives, A1 and A2. The two alternatives are chosen so that they can abstract approximately 10% more water than the present on/off pumps. A1 increases the capacity of Søndersø West. A2 decreases the capacity of Søndersø West and increases the capacity of Søndersø East. For A1, the optimization is performed for the case where the

Table 5.2: The different optimization runs. The low demand ($Q_{dem,L} = 432$ m^3/h) period is 3.11.2008-10.11.2008, and the high demand ($Q_{dem,H} = 638.7$ m^3/h) period is 03.03.2009-10.03.2009.

Run ID	Pump scenarios	Pump regulation	Q_{dem} [m^3/h]
1	Present	on/off	432.0
2	A1	variable-speed	432.0
3	A1	on/off	432.0
4	A2	variable-speed	432.0
5	Present	on/off	638.7
6	A1	variable-speed	638.7
7	A1	on/off	638.7
8	A2	variable-speed	638.7

pumps are operated as on/off pumps, and for the case where they are operated with variable-speed pumps. For A2, the optimization is performed with variable-speed pumps, only. Table 5.2 gives an overview of the different optimization runs and their run ID.

The results of the optimization are shown in Figure 5.5. First of all it can be seen that the H objective function for all optimization runs in the low demand period can be improved to positive values, securing a flow away from the well field. For the high demand curves only parts of the Pareto fronts become positive. It can be seen that the on/off pumps using the present pumps (ID1 and ID5) can provide some improvement in H, but very limited improvements in the specific energy, less than 3%. Changing the pumps to new variable-speed pumps greatly reduces the specific energy consumption, around 40% for the low demand and 25% for the high demand. To test if the decrease in specific energy is due to the variable-speed regulators or the new pumps, the optimization was performed using the A1 set of pumps, but with the restriction that they could be either on or off (ID3 and ID7). Figure 5.6 shows that the decrease in specific energy, using the new on/off pumps, is 8% for the low demand period and 11% for the high demand period, meaning that the main reason for the large improvement is optimization of the variable-speed regulators.

For further details see Paper III. Optimizing the on/off pumps is a discrete problem with a finite number of possible solutions. In Paper II the Pareto front obtain with the optimization is compared with an exhaustive benchmark solution.

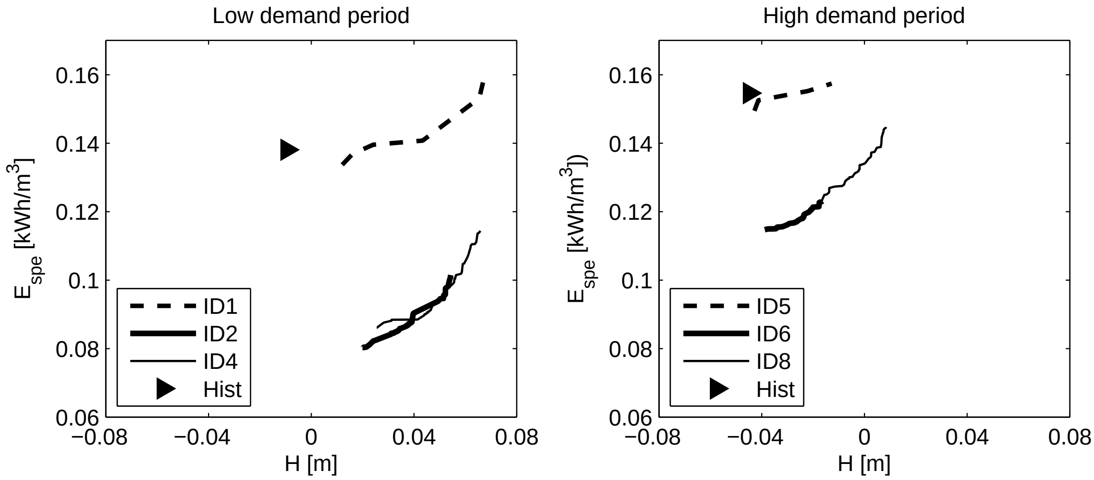

Figure 5.5: Pareto fronts for the different optimization runs in the low (left) and high (right) demand period. Legends refer to run ID in Table 5.2. Hist is the simulated history in the given period.

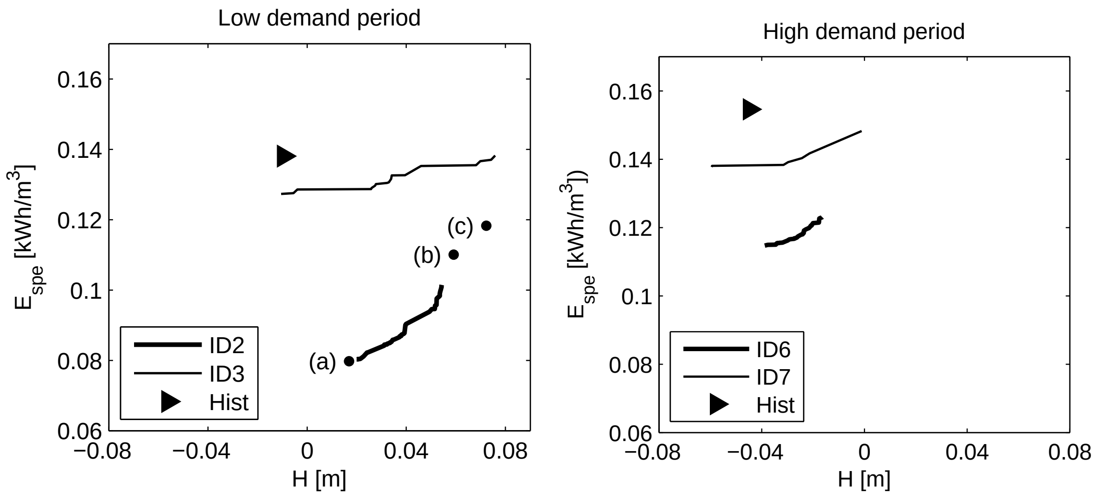

Figure 5.6: Pareto fronts for the different optimization runs in the low (left) and high (right) demand period. Legends refer to run ID in Table 5.2. Hist is the simulated history in the given period. (a) is minimum E_{spe} from single-objective optimization. (b) is maximum H for single-objective optimization. (c) is trial-and-error solution.

The solutions of the tails of the Pareto fronts of ID 2 and ID4 are shown in Figure 5.7. The most energy-efficient solutions are the lower left points on the Pareto fronts and are shown with white bars. The solutions with highest H are the upper right points on the Pareto fronts and are shown with black bars. The figure shows speed (s_i), pumping rate (q_i), power (p_i), and specific energy (e_i) for each well.

For the energy-efficient solution of ID2 the speed of the pumps (Figure 5.7.a1) is almost the same for all pumps (between 0.6 and 0.75). For the high H solution, the pumps at well 1, 9, 10, and 11 are turned down or off. These four pumps are closest to the contaminated area at Værløse Airfield, and turning them off reduces the risk of getting flow from the contaminated site towards the airfield. However, the remaining pumps have to operate with higher speed values to meet the demand, and the e_{spe}-values becomes larger.

For the ID4 run the distribution of the s_i-values (Figure b1) looks quite different due to the different pump types and capacities of the pumps. Six of the pumps in A2 are the high capacity pump SP95-4, and the pumps in well 3 and 6 are the low capacity pumps SP30-3 and SP27-5. For the high H solution the pumps closest to the airfield (well 1, 2, 9, 10) are turned off or down. Because of the higher capacity, the pumps in ID4 use slightly more energy than the pumps in ID2.

Figure 5.8 shows the solutions at the tails of the ID1 and ID3 on/off pump optimizations. When operating on/off pumps, more water than the demand is abstracted because of the discrete decision variables. The four solutions shown in Figure 5.8 abstract up to 60 m^3/h of water more than the demand. The variable-speed solutions abstract exactly the same as the demand. The abstraction of the extra amount of water does, however, not account for the large difference in power consumption between the on/off pumps (10-11 kW for each pump) and the variable-speed pumps (2-5 kWh for each pump). The reason is due to the affinity laws (Eq. 3.1) and the fact that the pumps can operate with a speed much less than 1 and still fulfil the demand.

Single-objective optimization for the ID2 run is used to find the tails of the Pareto front with respect to E_{spe} and H, respectively (Figure 5.6). The two points (a) and (b) are not far from the tails of the Pareto front. The ID3 on/off optimization does, however, finds solutions with much larger H-values than the variable-speed pumps. The reason that the variable-speed pump optimization does not find better solutions, is because of the large gap in the decision from a pump with $s_i = 0.6$ to a pump with $s_i = 0$. If the total amount of abstraction is close to Q_{dem} when the decision is taken, then the total amount of abstraction will decrease below Q_{dem}, and the solution is discarded in the EA.

By using trial-and-error it is possible to find a better variable-speed solution in just a few trials, point (c) in Figure 5.6.

Despite the difficulty of finding optimal H solutions for the variable-speed optimization, the method still provides solutions to the multi-objective problems, that

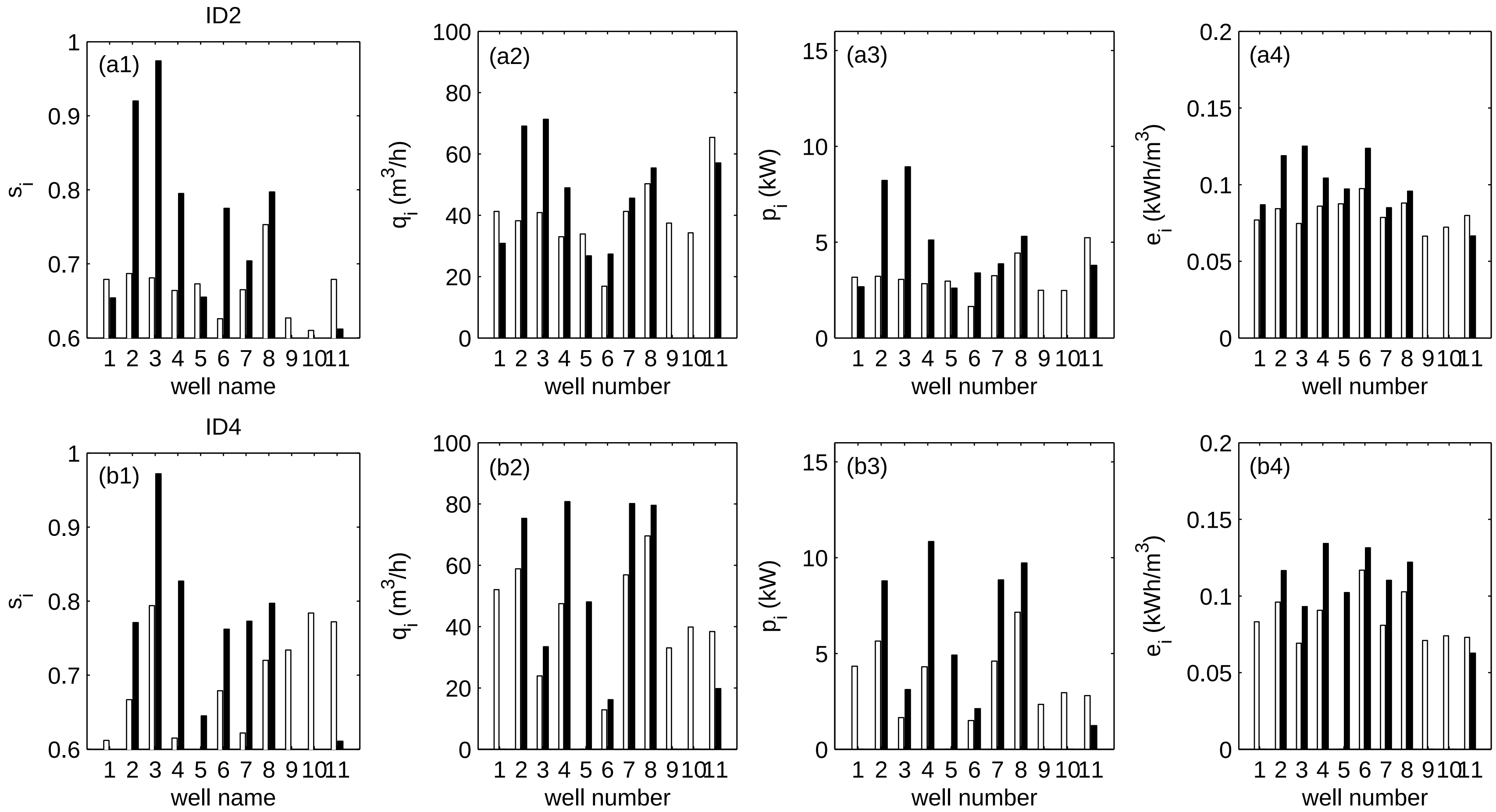

Figure 5.7: Upper row: A1, low demand (ID2). Lower row: A2, low demand (ID4). Columns: (s_i), (q_i) [m^3/h], (p_i) [kW], and (e_{spe}) [kWh/m^3]. Each bar diagram shows the values for each of the 11 wells. The white bars are the most energy-efficient individuals on the Pareto fronts (lower left). The black bars are the individuals with largest H value on the Pareto fronts (upper right).

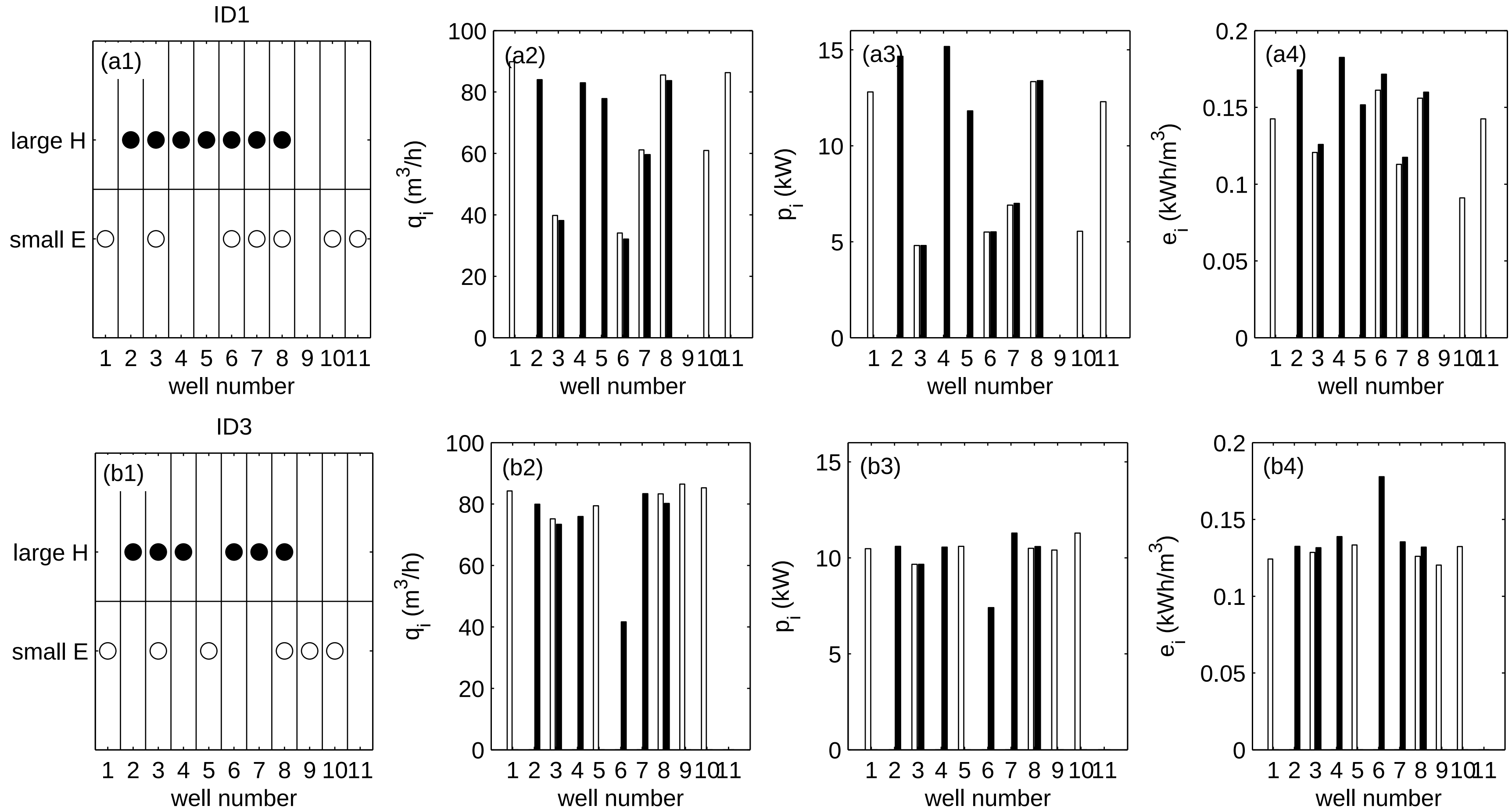

Figure 5.8: Upper row: Present on/off pumps, low demand (ID1). Lower row: A1 on/off, low demand (ID3). Column 1 shows the pumping configuration, a mark means that the pump is on, no mark means that the pump is off. Otherwise as for Figure 5.7.

Table 5.3: Reduction in energy consumption and payback period if new pumps are bought. The electricity price used in the calculation is 0.83 DKK/kWh and $Q_{dem,L}$ and $Q_{dem,H}$ as in Table 5.2.

	Price pumps [DKK]	min E_{spe} [kWh/m^3]	Energy reduction [MWh/years]	Payback [years]
ID2: A1, $Q_{dem,L}$	570,592	0.080	219	3.1
ID6: A1, $Q_{dem,H}$	570,592	0.115	224	3.1
ID4: A2, $Q_{dem,L}$	676,160	0.086	197	4.1
ID8: A2, $Q_{dem,H}$	676,160	0.120	196	4.2

are significantly better than the historical operation. It would therefore be an advantage for the waterworks, if they changed the pumps to new variable-speed pumps.

The cost of buying the 11 new submersible pumps, with variable-speed regulators, is approximately 0.5 million DKK (1 EUR = 7.46 DKK). The payback period will be 3-4 years due to the reduction of about 200 MWh per year in electricity consumption. See Table 5.3 for details of the different alternatives. The water utility normally makes investment with payback periods less than 5 years, so buying the new pumps is realistic. It is interesting to note that the energy saved is almost the same for the low and high demand.

5.2.3 Energy savings on national basis

The specific energy consumption of the Danish waterworks spans a rather larger interval, from 0.1 to 0.6 (Refsgaard et al., 2009b). Søndersø waterworks has without optimization an energy consumption of 0.14 and is though, in comparison with the other waterworks quite energy efficient. Because large savings could be obtained at Søndersø waterworks there is reason to believe that the potential for saving energy on national basis is large.

The Danish waterworks abstracts yearly approximately 406 million m^3 of water (Thorling, 2010), and the average specific energy consumption is 0.2 kWh/m^3 (Refsgaard et al., 2009b; Reschefski, 2009). The results from Søndersø showed a potential saving of 25 to 40% of the specific energy. If similar saving in the specific energy could be obtained on national basis, the yearly saving will be between 20 and 32 GWh, or 17 to 27 million DKK.

6 Conclusion

The aim of this research was to investigate improvements at well field management with respect to different conflicting objectives using multi-objective evolutionary algorithms.

A framework that can perform multi-objective optimization on the management of well fields was developed. A constant and a sequential scheduling optimization was used. The latter is a novel approach to performing multi-objective optimization in a real-time situation and, to our best knowledge, it has not been applied before.

The multi-objective optimization framework was tested successfully in two case studies, Søndersø waterworks and Hardhof waterworks. The objective functions in the two case studies are different, but the optimization framework provides the opportunity to change or add objective functions according to the specific case studies.

The objectives for the Hardhof waterworks were to minimize the infiltration and to minimize the contamination risk. The contamination risk is quantified by maximize the differences in head observations (H). Basins and wells are used for artificial infiltration. The infiltration serves multiple purposes and is essential for the operation of the waterworks, because it creates a barrier towards the contaminated area and it enhances the residence time of the water in the aquifer (compared to use the water from directly from the river bank filtration wells). If the infiltration is decreased too much, the barrier will disappear and contaminated water will flow into the production wells.

The two optimization methods were applied and tested under dry and wet hydrological conditions. All optimization runs show that it is possible to improve both objectives compared with the historical operation. If H is kept at the historical level the total infiltration can be reduced by 27% during the dry period. To increase H the distribution of infiltration must be changed so that more water is infiltrated in the basins and less in the wells. However, to obtain the desired positive H values it is necessary to increase the total infiltration with at least 20%. Constant scheduling performs best in stable hydrological conditions with fairly constant water demands. Sequential scheduling performs best when the hydrological conditions are highly variable.

The objectives of the Søndersø waterworks case study were to minimize the energy consumption and to minimize the contamination risk from a nearby contaminated site. The latter was quantified by maximize the head differences at a number of points along the water divide between the well field and the contaminated area. It is desired to get positive head difference values to ensure a flow of water away from the well field.

A WELL Field Numerical Engine Shell (WELLNES) model was to set up and calibrate for the area. The model is unique, because it is a fully integrated hydrological and hydraulic model which simulates the flow of water in the aquifer, in the wells, and in the pipe network. The WELLNES model shows good correspondence between observations and simulations.

Optimizing the pumping configuration using the present on/off pumps shows that the contamination risk could be reduced, but only minor savings in the energy could be obtained. Changing the on/off pumps to variable-speed pumps greatly improves both objectives.

For the low demand period the entire Pareto front obtains positive head difference values, hence securing a flow towards the contaminated area. For the high demand period only a part of the Pareto front obtains positive head difference values. The specific energy can be reduced with around 40% for the low demand period and 25% for the high demand period. Both corresponding to a reduction in the energy consumption of approximately 200 MWh/year. The cost of acquiring 11 variable-speed pumps is around 0.5 million DKK, which would be paid back in only 3 to 4 years due to the energy savings.

The research illustrates that well field management can be improved by using multi-objective optimization. The Pareto front makes it simpler for the decision-makers to choose the best management solution. The decision-makers can chose one of the Pareto optimal solutions, knowing that it is indeed an optimal solution and knowing the objective functions values for the given solution.

7 Outlook

The optimization framework can be adapted to other groundwater management problems with other objectives, like saltwater intrusion, groundwater depletion, water quality or considerations of the aquatic environment.

If further work should be done on the Søndersø case it would be interesting to investigate the impact on the aquatic environment in the streams around Søndersø due to the substantial abstraction from the area.

The sequential scheduling optimization used in the Hardhof case could also be redesigned to perform optimization for larger time periods than the actual time step. This would avoid the present disadvantage of highly varying solutions, but use the advantages of both the constant and sequential scheduling.

Another future prospect that could benefit the optimization is to use parallel computing. Multi-objective optimization is very well suited for parallelization, and it would make it computationally feasible to optimize longer time periods or problems with time-variable decision variables in real time.

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9 Papers

I. Hansen, A.K., Hendricks Franssen, H.J., Bauer-Gottwein, P., Madsen, H., Rosbjerg, D., Kaiser, H.P. *Well Field Management Using Multi-Objective Optimization*, submitted manuscript, February 2011.

II. Hansen, A.K, Madsen, H., Bauer-Gottwein, P., Falk, A.K.V., Rosbjerg, D. *Multi-objective optimization of the management of a waterworks using an integrated well field model*, Hydrology Research, 2011, accepted

III. Hansen, A.K, Madsen, H., Bauer-Gottwein, P., Rosbjerg, D., Falk, A.K.V. *Optimization of well field operation: Case study Søndersø waterworks, Denmark*, submitted manuscript, June 2011

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